

VALIDATION OF A CANCER READMISSION PREDICTIVE MODEL

A Honors Thesis

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Abstract

Cancer patients are at a high risk of hospital readmissions due to the complex nature of the disease. Currently, there is not a reliable predictive measure to assess hospital readmissions in cancer patients, but there have been attempts to determine readmissions based on other factors. The purpose of the study is to determine whether or not assigning a logistic model driven risk score to a patient at the time of discharge is an accurate predictor of readmissions, and to determine which additional factors influence readmissions. If assigning a risk score at the time of discharge is an accurate predictor of readmissions, it could allow other cancer designated hospitals to implement a similar predictive model. Predetermined variables were extracted from patient medical records within the Electronic Health Record (EHR), and these variables were compiled into a database where a predefined algorithm was implemented to calculate patient risk scores.

The predicted likelihood of a readmission was then compared to the actual 30-day readmission status of the patients as a measure of the reliability of the risk score. After a data analysis was conducted, it was found that the readmission predictive model was accurately predicting readmissions based on a Chi-Square test ($p < 0.001$). The Kappa score for the agreement between actual readmission and the patient's assignment to a high risk category was 0.125, which is a low Kappa score, and shows that there is work to be done to make the model better at predicting readmissions.

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Chapter I: Introduction

Problem Statement

“Necessary evil or preventable target for quality improvement?”¹ Cancer patients are at a high risk of hospital readmissions due to the complex nature of the disease. It is critical to determine whether hospital readmissions among cancer populations are preventable. With advancing technology, clinical trials, and research, there is hope that an accurate readmissions model will be created to forecast preventable readmissions. An accurate model could reduce readmissions and improve the quality of life for cancer patients. Patients who encounter readmissions have increased cost of care associated with their stays, owing to subsequent encounters. Discovering a way to reduce readmissions rates, will make the financial cost of care less burdensome. This disease is impacting the lives of many individuals and their families, and although there is not a cure for every type of cancer, many researchers are trying to find a way to predict what drives readmissions amongst cancer patients to better understand the disease. According to the Surveillance, Epidemiology, and End Results (SEER) Program, the estimated number of new cancer cases in 2014 was 1,665,540, with an estimated 585,720 cancer related deaths.² And, in 2011, the estimated number of people living in the United States who were living with cancer was estimated to be 13,397,159.² The statistics above demonstrate the impact of cancer on the health of our nation.

Although there are no reliable predictive measures to assess hospital readmissions in cancer patients today, Dr. Susan White and colleagues at The Ohio State University have created a 30-day cancer readmissions predictive model. Their cancer readmission predictive model is now in its validation phase. The validation of the model is essential because it could be the first of its kind. By implementing this model, it is possible preventable measures could be taken to prevent readmissions at cancer-designated hospitals. Diminishing readmissions could reduce the cost of care and reform the comprehensive patient experience. The idea of increasing quality care and decreasing cost has been the primary focus for the Institute of Healthcare Improvement. Their aspiration is to optimize performance within our healthcare system, and strive to reach this goal by developing a framework known as the “Triple Aim.”

The three fundamental parts to the Triple Aim framework include “improving the patient experience of care (including quality and satisfaction), improving the health of populations, and reducing the per capita cost of health care.”³ The development of a readmissions model could assist with implementing the Triple Aim approach in our healthcare system. Today, there is not a dependable predictive measure to assess hospital readmissions in cancer patients, but there have been attempts to determine readmissions based on other factors, such as procedure complications, socioeconomic status, underlying conditions, and select cancer types. If there is a way to foresee unintended hospital readmissions, it could assist researchers and doctors gain a comprehensive

understanding of cancer treatment and preventative care. A reduction in readmissions for cancer care is in alignment with all three of the IHI Triple Aims.

Furthermore, hospital readmissions are a significant concern from a quality standpoint, and a focus for the Centers of Medicare and Medicaid Services (CMS). CMS has established a new regulation to reduce payments given to inpatient prospective payment system (IPPS) hospitals if they have an excessive volume of readmissions compared to the average readmission rates of the majority of inpatient hospitals. Currently, CMS is only focusing on the readmission ratios for Acute Myocardial Infarction, Heart Failure, and Pneumonia.⁴ While this system does not apply to cancer readmissions at this time, it demonstrates the importance of understanding hospital readmissions and providing exceptional quality care to all patients.

By developing a predictive model and assigning a risk score to every cancer patient at the time of discharge, it is possible to predict readmissions among cancer patients and determine the reasoning behind them. Cancer patients are at a higher risk of readmission,¹ but there has not been a readmissions model specifically designed for the cancer niche. Compared to the general population, cancer patients are at a considerable risk of readmissions, but in this study we focused on the readmissions among cancer patients alone by scoring them as being at a high/low risk based upon a predictive model.

Purpose of the Study

The purpose of the study was to determine whether or not assigning a logistic model driven risk score to a patient at the time of discharge was an accurate predictor of readmissions, and to determine additional factors that influence readmissions. If assigning a risk score at the time of discharge is an accurate predictor of readmissions, it could allow other cancer designated hospitals to implement a similar predictive model.

Significance of the Study

This research is significant to the Health Information Management (HIM) field and the healthcare field in general. The predictive model puts a prime focus on reducing readmissions and demonstrates the technical advancements in the medical information technology field, which has allowed for this predictive model to be created. The significance of the study was to allow IT, HIM professionals, and healthcare providers to work together to implement and practice a readmissions model, and attempt to move forward in predicting readmissions in cancer patients, determining driving factors behind readmissions, and developing ways to practice optimal and preventative care. The overall significance was to determine if assigning a logistic model driven risk score to a patient at the time of discharge was an accurate predictor of readmissions and to find a way to apply the results from the model to everyday cancer admissions at NCI designated cancer hospitals.

The research that has been explored on hospital readmissions has not chiefly focused on cancer patients alone. The collection of research that has been conducted on hospital readmissions has been rendered on general hospital readmissions, or has focused on readmissions for non-cancer related diseases. “Chronic diseases and conditions—such as heart disease, stroke, cancer, diabetes, obesity, and arthritis—are among the most common, costly, and preventable of all health problems.”⁵ Not only is cancer one of the most common chronic conditions in the United States, it is one of the most costly. According to the National Cancer Institute, the costs of cancer care accounted for \$157 billion in 2010.⁶

Although the occurrence of cancer readmissions have received inconsiderable attention, there has been a minuscule amount of research conducted on how to predict and potentially avoid cancer readmissions. The primary focuses of the conducted studies were on procedure complications and/or specific cancer types. Instead of using a readmissions model to anticipate hospital readmissions, researchers have focused primarily on readmissions related to specific cancer related procedures, and attempting to correlate readmissions with cancer survival rates. At this time, there is currently a gap in research in discovering a reliable predictive measure to gauge readmissions between cancer patients.

Objectives of the Study

My research questions are as follows:

- 1. Is using the readmissions model and risk score an accurate predictor of hospital readmissions among cancer patients?**
- 2. Is there a correlation between a higher risk score and the likelihood of readmission?**
- 3. If patients were assigned a low-risk score, but were readmitted, did the discharge disposition have an affect on the readmission?**
- 4. Are cancer patients within a particular service area more likely to be readmitted in comparison to those within another service area?**

The above research questions will aid in determining if the readmissions model is an accurate predictor of cancer readmissions. These questions will help discover if the readmissions model Dr. White and colleagues created, is an accurate model in predicting readmissions and to determine if they should move forward with implementing the model within electronic health records (EHR) at cancer designated hospitals, specifically The Ohio State University James Cancer Hospital and Solove Institute. The hypothesis was that the model would be an accurate

predictor of readmissions and would pass the validation phase to move forward with the implementation of the model.

Limitations

Limitations of the study included not being able to conduct a data analysis on a higher encounter volume due to constraints with the timing of graduation. A 12-month run out of data would have made the study stronger. Furthermore, the timing of creation of the IT build in EPIC, prevented additional data from being used in my data analysis. The build was input into EPIC later in the year than what was originally intended.

One of the biggest limitations involved the cutoff of scores used in the model. When the model was being validated in the Excel database, the risk scores went out to four decimal points. Due to restrictions in the EPIC system, the scores had to be cutoff to two decimal points. Because the risk scores had to be cutoff, there is a possibility the scores did not capture patients to the full capacity when assigning them a risk score, which reflects how likely they were to be readmitted. It is possible that patients in the high-risk category would have been in the low-risk category if the decimal points went out four places and vice versa. A closer look will need to be made to make sure the cutoffs are aligned accordingly and look for ways to improve them.

Chapter II: Literature Review

When conducting my literature review, there were many articles which pertained to cancer readmissions; however, there is currently no exact measure that has been found to strongly predict cancer readmissions. In numerous studies, researchers have tried to narrow down cancer readmissions based on particular types and stages of cancer. Other studies have tried to correlate sex and various surgical procedures used to cure and/or treat cancer. Although there has not been a measure found to predict all cancer readmissions, it is possible that predictive measures for specific cancers could be narrowed down to an overall predictive measure, which could be applied to all types of cancer. Cancer is becoming more and more prevalent and there is a need to prevent readmissions.

Keywords: cancer readmissions, cancer readmissions predictor, readmissions measures, quality, hospital readmissions, cancer predictive model

Hospital Readmissions

A hospital readmission is defined as “multiple inpatient stays within a specified time period by the same patient. Sequential hospital visits may occur for any reason and can be separated by days, weeks, months or years.”⁷ For the purposes of this study, an admission within 30 days of a previous discharge from an inpatient stay is defined as a readmission.

Hospital readmissions have been in the spotlight as a target for quality improvement. It has been a controversy as to whether or not hospital readmissions are considered a negative factor in the healthcare field. Some individuals see hospital readmissions as a way of reflecting poor quality care to the patient before discharge, and others see it from the other perspective that they are non-preventable readmissions, which cannot be controlled, causing a patient to be readmitted.

The article, *Hospital Readmissions: Necessary Evil or Preventable Target for Quality Improvement*¹ by Erin G. Brown et. al., focused on 30 day readmissions on cancer patients to try to determine driving factors behind hospital readmissions. In their research, they found many reasons for readmissions of cancer patients that were not preventable, but there were a few factors which could have been prevented. The factors they found to be preventable included nausea, dehydration, pain, and vomiting. These factors, if treated properly or monitored before discharge, may have prevented patients from being readmitted to the hospital.

Although the root causes could have been prevented, of all of the readmissions, “33% ... were due to potentially preventable problems such as nausea, vomiting, dehydration, and postoperative pain.”¹ From a quality stand point, some healthcare providers see decreased length of stay (LOS) at the hospital to be a driving factor of readmissions; however, in this study, the opposite effect was observed on readmissions. Brown and

researchers saw longer length of stays were associated with readmissions. It was hypothesized that a greater length of stay was associated with a greater likelihood of readmission due to the complexity of postoperative complications. However, when Brown and colleagues ran a regression analysis on their patient data, the analysis showed a weak relationship between length of stay and hospital readmissions. Some believe that readmissions are due to patients being discharged too early, so hospitals can see more patients in a shorter period of time for greater financial reasons. Also, some patients leave against medical advice and prefer to be discharged earlier than they should be, so they do not have large hospital bills. Readmissions are an ongoing debate, and it's controversial as to whether or not readmissions can truly be prevented, bringing about the question, "Necessary evil or preventable target for quality improvement?"¹

Hospital Readmissions Model

Over the years, researchers and healthcare professionals have tried to develop a way to predict hospital readmissions by creating predictive models. The idea behind a predictive model is to look at various factors, which might put a patient at a higher risk of being readmitted and try to determine a way to minimize readmissions based on those factors. In the research article, *Hospital Readmission in General Medicine Patients: A Prediction Model*,⁸ researchers created a prediction model "to identify patients with significantly elevated readmission risk."⁸ The researchers focused on factors, which put patients at a

higher risk of readmissions. Hansan and colleagues categorized the risk factors into four categories, 1.) socioeconomic factors, 2.) social support, 3.) health condition, and 4.) healthcare utilization. In their model they looked at factors from diverse spectrums, instead of focusing on only the patient's health condition. Based on factors within these four categories, researchers assigned patients a risk score. The scores were determined by "entering each patient's risk score into a single predictor logistic regression model and used the output from this model to determine score cutoffs for identifying patients within selected readmission risk levels (0-9%, 10-19%, 20-29%, and 30% or higher)."⁸ In the validation of Dr. White's model the focus of the model also involved assigning patients a risk score, but the primary focus was on the patient's health and other health related conditions known at the time of discharge, and focused on cancer patients specifically, rather than general medicine patients.

Diagnosis-Specific Readmission Model

Many hospital readmission models have had a centralized focus on hospital readmissions as a whole, rather than applying a focus on diagnosis and disease specific readmissions. In the research article, *Diagnosis-Specific Readmission Risk Prediction Using Electronic Health Data: A Retrospective Cohort Study*,⁹ Hebert and researchers hypothesized that creating a readmissions model that was specifically designed for a particular disease type, would be a more accurate model in predicting readmissions,

rather than using a model, which combines multiple disease types into one predictive model. Hebert's team also hypothesized that a model specifically created for their institution, would be more accurate in predicting readmissions.⁹ In this study, Hebert and researchers created four readmission models. The models they created consisted of three diagnosis specific models and one model which combined the three diagnosis specific models. The three diagnoses included in these models included congestive heart failure (CHF), pneumonia (PNA), and acute myocardial infarction (AMI).

The data collected for the readmission models was retrospectively collected from The Ohio State University Wexner Medical Center's (OSUWMC) information warehouse (IW). From the information warehouse, Hebert and researchers collected both administrative and clinical data. The data they collected included patient demographics, comorbidities, medication orders and lab results, and the patient's social history.⁹ Their models used a logistic regression approach, and were able to conclude that the "...disease-specific models generally performed better than the combined."⁹ The reason why they think the disease-specific models performed better than the combined model was due to the differences in the complexity and characteristics of the different diseases.

This research concept is similar to the concept used in my research in that it focuses on disease-specific diagnosis models to predict 30 day readmissions, and that "these models are the first step in a plan to embed a tool into [their] comprehensive electronic

health record (EHR) to alert physicians to high risk patients at the point-of-care.”⁹ Dr. White and colleagues focused on developing a disease-specific readmissions model for predicting readmissions of cancer patients. By doing so, a build was created within the EHR to assign and track the patient’s risk score. The build was a new technological feature created within the architecture of the EHR. The build was designed to generate the risk score based on select variables calculated from an algorithm. The variables included in the readmission model are as follows: length of stay (LOS) greater than five days, emergency admission vs. non-emergency admission, GI cancer diagnosis, solid tumor diagnosis, surgical vs. non-surgical services, abnormal sodium levels, abnormal white blood cell count, abnormal hemoglobin levels, emergency department visit within the last 30 days, and being previously admitted to the hospital within the last 60 days. These combined variables were used to calculate the risks score using the algorithm in the EHR.

Although Hebert’s research had the general idea of incorporating the readmission models into their EHR, it had not been accomplished to see how the two work together to “...alert physicians to high risk patients at the point-of-care.”⁹ In the cancer predictive model, the information collected was real-time, rather than retrospectively collected from the information warehouse. We were also looking to incorporate a build within the EHR for the risk assessment model for readmissions. Also, in their study, cancer was considered to be a comorbidity rather than being the disease specifically receiving

research attention. The primary focus of Dr. White's model was on cancer patients as a whole, so cancer was the primary focus, rather than being identified as a comorbidity. Hebert's research did have a common factor to the research we conducted in that the overall goal was to create a readmissions model to accurately predict readmissions.

Providers Predicting Readmissions

Predicting hospital readmissions are primarily predicted based upon designated readmission models. In the research article, *Inability of Providers to Predict Unplanned Readmissions*,¹⁰ researchers took a different approach in predicting hospital readmissions. Instead of developing a specific readmissions model to predict readmissions, researchers asked inpatient employees, involved in patient care, to estimate the likelihood of their patient being readmitted to any acute care hospital within 30 days after discharge from their facility.¹⁰ One of the primary reasons why the researchers chose not to use a risk assessment tool was due to the fact that "providers may incorporate important factors not easily translated into variables and therefore omitted from prediction tools, such as socioeconomic factors, health literacy, or even unmeasured clinical variables."¹⁰ These factors are not the easiest factors to translate into a uniform variable to try to predict readmissions. In this study, Allaudeen and colleagues did not take the approach of implementing a readmissions model, but instead, relied heavily on readmission

predictions from physicians, nurses, case managers, and residents for readmission predictions.

Not only did they focus on the likelihood of a patient being readmitted, they also focused on predicting the probable cause of a patient being readmitted. Although providers are able to diagnosis and treat patients on their initial visit, they are not able to accurately determine the likelihood of readmissions or the causes behind them. In their study, they concluded that provider groups were unable, with confidence, to predict whether or not a patient would be readmitted to the hospital, and among all provider groups, none of the providers accurately predicted the root cause of a patient being readmitted.¹⁰ Predicting unplanned readmissions has not been seen as an easy task, but researchers continue to try to develop different ways and ideas to predict them. There has been pressure to reduce hospital readmissions, and “amid increasing pressure to reduce readmission rates, hospitals do not have accurate predictive tools to guide their efforts.”¹⁰

Unplanned Hospital Readmissions in Cancer Patients

Hospital readmissions in cancer patients has not been examined in full, and according to the research article, *Risk for Unplanned Hospital Readmissions of Patients with Cancer: Results of a Retrospective Medical Record Review*,¹¹ Weaver and researchers, stated that after conducting “...an extensive literature review, published studies

examining predictors of hospital readmission specifically for patients with cancer in the United States were not found.”¹¹ Although their research was done a few years ago, it still holds true that there has not been much research conducted on cancer readmissions. In their study, they focused on seven day readmissions of cancer patients by conducting a retrospective medical record review. The researchers created a “Readmissions Criteria Record for data collection.”¹¹ The Readmissions Criteria Record was a “82-item, two page instrument” and “was designed to collect demographic information as well as possible risk factors for readmissions.”¹¹ Within this instrument, they created specific categories designated to age, home and family, coping and adaptation, concrete, and various other categories, and then listed potential risk factors associated with each category.

Weaver and colleagues believe nurses should be educated on the reasons why cancer patients are more likely to be readmitted to the hospital, and that patients should be educated on how to prevent any problems associated with their disease and its treatment. They also emphasized the importance of patients knowing how to contact their healthcare provider if symptoms occur, and that nurses should know how to identify any risks which may cause a patient to be readmitted, before discharging them.¹¹ In this study, it emphasized the importance of the ability for medical providers to understand the patient’s disease, as well as making sure that the patient is educated about follow-up care after an inpatient hospital stay. Developing a predictive readmissions model for the cancer

population might not find a cure for the disease, but it could help patients and healthcare providers understand the various risk factors, which lead to readmissions and how to prevent those readmissions from occurring.

In their study, Weaver and colleagues found that the most common factors associated with readmissions were nausea, not having easy accessibility to a caregiver, not being able to afford treatment due to financial means or not having insurance, living alone and not having someone to watch over them, and those with GI cancer.¹¹ Although these are all valid risk factors driving readmissions, this differed from our study because a risk score was not created for patients based on their risk factors to see their likelihood of readmission. One key point from this article, is that the researchers addressed that “people with cancer are a special population, often with complex care needs as well as psychosocial issues.”¹¹ Since cancer patients are considered to be a unique population, it is important that their needs are addressed based upon their condition. A readmissions model designed specifically to cancer, would allow researchers, physicians, and patients to gain a better understanding of the disease and other factors which may put them at a higher risk of readmission. Identifying risks of potential readmissions and educating patients before discharge could decrease readmission rates.

CMS Hospital Readmissions Reduction Program

The Hospital Readmissions Reduction Program went into effect on October 1, 2012 penalizing providers for discharges. The program was “mandated by the Affordable Care Act, [and] requires the Centers for Medicare & Medicaid (CMS) to reduce payments to IPPS hospitals with excess readmissions.”¹² This initiative was established to emphasize the quality of patient care, and by doing so, imposing a monetary penalty. As of now, cancer has not been one of the diseases that CMS is focusing on for monetary penalties.

For fiscal years 2013 and 2014, CMS focused on 30 day readmissions of Acute Myocardial Infarction (AMI), Heart Failure (HF), and Pneumonia (PN). For fiscal year 2015, CMS has penalties for readmissions for chronic obstructive pulmonary disease (COPD) and elective hip arthroplasty (THA) and total knee arthroplasty (TKA). These penalties will be distributed for these diseases and procedures if the hospital has an excessive amount of readmissions “compared to the national average for the hospital’s set of patients with that applicable condition.”¹² Each fiscal year, the percentage of the penalty increases, with 3% being the maximum. The Hospital Readmissions Reduction Program has and continues to emphasize the importance of decreasing hospital readmissions.

Readmissions Following Surgical Procedures

Most research that has been conducted on readmissions has been based on surgical procedures. It is likely that complications may arise after being discharged from a surgery, and it can also be seen that not all patients react to surgical procedures the same way. In the article, *Predictors of Readmission following Outpatient Urological Surgery*¹³ by Aksharananda Rambachan, Richard S. Matulewicz, Matthew Pilecki, John Y. S. Kim, and Shilajit D. Kundu, they focused their research on readmissions after urological surgery and categorized complications based on medical and surgical complications.

In this study, Rambachan analyzed multiple factors that influenced the readmission rate of patients following urology surgeries. In their research they found that patients with comorbidities such as diabetes, dyspnea, and COPD were more likely to be readmitted. “Risk adjusted multiple regression analysis revealed that history of disseminated cancer, bleeding disorder, ASA physical status 3 or 4, male gender and age were statistically significant predictors of readmission. Cancer carried the greatest risk of readmission.”¹³ In this study, although it focused on the complications and factors which drive readmissions after surgery, it demonstrated that cancer puts patients at a higher risk of readmission. This is why it is important to develop and implement a readmissions model specifically designed for the cancer population. Since they are already at a higher risk than the general population, it would be beneficial to see what drives readmissions within their own designated population.

After conducting an in-depth literature review, it was found that little research has been conducted on predicting 30-day unplanned readmissions in cancer patients. Predictive modeling is one of a kind and can bring valuable knowledge to clinical and analytical research. Many of the studies I reviewed included the creation of a predictive model for readmissions, but were not designated for the cancer niche. With cancer being an intricate disease, the current predictive models that are being used in other health systems, cannot properly assess cancer patients and accurately predict a readmission. Models exclusive to overall readmissions, puts patients with a cancer diagnosis at an absolute high-risk of readmission. At this time, there is no written or electronic information regarding a predictive model used in a specific cancer designated institute.

Definition of Terms

The following terms were used throughout the study:

- **Risk Assessment Score-** a score given to a patient to determine their risk of being readmitted based on specific medical factors.
- **Readmissions Model-** a model used to predict the likelihood of a patient being readmitted based on select factors.
- **Surveillance, Epidemiology, and End Results Program (SEER)-** Is a program that is a part of the National Cancer Institute. It provides cancer statistics for the United States' population.

- **CMS**- Centers of Medicare & Medicare Services
- **National Cancer Institute (NCI)**- Supports and conducts cancer research.
- **EMR**- Electronic Medical Record
- **Healthcare Cost and Utilization Project (HCUP)**- Database containing healthcare data for state, local, and national levels, which assists in research.
- **LOS**- Length of Stay
- **Readmission**- Being admitted to an inpatient hospital within 30 days after discharge following an initial visit
- **IHIS**- Integrated Healthcare Information System
- **Build**- A new technological feature created within the architecture of the EHR to generate risk scores based on select variables calculated based on a premade algorithm
- **SPSS**- Statistical Software for the Social Sciences
- **Midas**- A case management software program that follows a patient through out their stay and allows for data collection and reporting
- **Microsoft Access**- A database management software which allows for data reporting and report building

Chapter III: Methodology

The methodology chapter will begin by discussing the research design and data collection procedures, and then conclude with a summary of the data analysis.

Research Design

The research design consisted of assigning cancer patients a logistic model driven risk-score at the time of discharge in attempt to determine if the risk-score was an accurate predictor of hospital readmissions. The algorithm in the EHR updated the risk score every morning at 1:00AM. If there were any significant changes in the predefined variables that would affect the score, the updated score would be reflected on the following day. It was acknowledged that the length of stay would increase each day, and a longer length of stay was a factor in the model used to estimate a patient's probability of being readmitted. The other variables comprised in the calculation of the logistic model driven risk-score were emergency admissions, presence of gastrointestinal cancer, surgical vs. non-surgical services, abnormal sodium levels, abnormal white blood cell count, abnormal hemoglobin levels, solid tumor diagnoses, patients previously admitted to the hospital within the last 60 days, and patients who have had a visit to the emergency department within the last 30 days.

The data used consisted of discharged patients between November 18th, 2015 and December 31st, 2015. By pulling discharge data from this time period, it allowed us to conduct a research analysis on 1,226 hospital encounters as well as having a thirty day run out in order to determine if the discharged patients were readmitted. I extracted the data from the EHR and applied it to the model in the Excel database. Once all of the variables were extracted from the medical record, a “-1” was entered into the Excel database under the select variable’s column, if it did not put the patient at a high-risk, and it was considered to be protective and reduced the predicted probability of readmission. These were considered negative predictive values. A “1” was entered when any variable put a patient at a higher risk of readmission, and was considered to be a positive predictive variable. By entering “-1” and “1” into the algorithm equation in the Excel database, it was able to calculate the correct readmission score for the patient, and the cell containing the calculation was conditionally formatted to account for the colored categories that identified the patient’s likelihood of readmission (green, yellow, red, & black).

If there were any discrepancies in the score in the Excel database compared to the score generated in the EHR, a thorough analysis was done to identify which variable, if any, were being calculated differently in the EHR than in Excel. If there were any discrepancies that could not be identified, a screenshot was taken of the two scores, and was discussed as a group, and our Senior Systems Consultant was consulted as needed to

make any minor changes to the model, to ensure the model was optimally performing and was reading the variables correctly to generate the risk score. We wanted to see if patients with higher risk scores were more likely to be readmitted in comparison to those with lower risk scores.

The algorithm created within in the EMR generated the risk score daily for each patient. The score was displayed on the patient's chart in the form of a colored code. The colored tiers consisted of red, yellow, green, and black, similar to a traffic light. The green color correlated to a low likelihood of readmission, and yellow correlated to a medium/ fair probability of readmission, followed by red and black. The black colored tier correlated with the highest possibility of the patient being readmitted, with an almost guarantee that the patient would be readmitted. When analyzing the data, the colored categories were transferred into low-risk and high-risk categories, rather than breaking it out by each color. The green and yellow categories were combined to create the low-risk pool of patients, and the red and black categories were combined to comprise the high-risk pool. The original cutoff categories can be located in **Table 1** below. In our data set, the scores were cutoff to two decimals points due to the build in the EHR. In our data set, the high-risk category was comprised of scores ranging from -0.44 to -2.18, and our low-risk category was comprised of scores ranging from -2.19 to -3.84.

Cancer Risk Score Cutoffs	
Green	< -2.4423
Yellow	≥ -2.4423 and < -2.1972
Red	≥ -2.1972 and < -1.3863
Black	≥ -1.3863

Table 1: Cancer Risk Score Cutoff Categories

If a clinician or nurse were to open the patient's record, they would see a colored circle, which correlated with the odds of the patient being readmitted. Anyone involved in the patient's care could hover over the colored circle in the record to see which variables were used to calculate the logistic model drive risk-score, and what the patient's overall generated risk score was. Risk scores did not change significantly each day, but they did change significantly over time.

Risk scores were monitored for any patterns where the colored tier and the likelihood of readmission do not align as expected. An analysis and investigation was done on factors that may have caused a patient with a green or yellow risk score to be readmitted. By looking into the factors which caused an unexpected readmission in the low-risk area, it will help improve the model moving forward.

Once the validation of the scores in the EHR aligned with the scores in the Excel database, a Systems Analyst in the IW was consulted to create monthly reports, which included the patient's last recorded risk score upon discharge. The information included

on the monthly reports included the patient's account number, medical record number (MRN), patient's name, service name, discharge unit, providers name, admission type, hospital admission time, hospital discharge time, length of stay, risk scores, lab values, and the recorded time of the patient's risk score. After receiving reports created by the Systems Analyst, an Access database was created to link the Monthly Readmission Risk Score Report from the Information Warehouse with a readmissions report from Midas.

The monthly report showed all discharged James' patients with a cancer diagnosis, excluding Sickle Cell patients, benign tumors, and patients with a discharge disposition of expired. The readmissions report from Midas showed any and all James readmissions. An access database was created to link the two Excel reports to track of those patients who were seen in the prior month, which of them were readmitted within 30 days. After determining which patients had been readmitted, a data analysis was conducted to see which of the four risk score colored categories each patient fell into upon discharge. This allowed us to see what percentage of patients readmitted within 30 days of discharge fell within each category.

Issues did arise when validating the risk scores calculated in the EHR. One issue reflecting the build, was the length of stay not calculating correctly. The original build in the EHR was built to put a patient at a higher risk of readmission, if the patient had a length of stay greater than or equal to 5 days. The build was not correctly calculating the

score because the patient should not have been put at a higher risk until they had reached a length of stay greater than 5 days.

The Excel database was built correctly to account for this variable, but the EHR build was not carefully assessed to make sure it was accounting for this variable in the same way. A correction by an IT professional was made to the system to calculate the length of stay correctly. By correcting the build, the system now identifies patients with a LOS greater than 5 days to be at a greater risk, rather than including the 5th day.

Another issue that arose in the build, which caused a discrepancy, included the patient's lab values for hemoglobin, sodium, and white blood cell count. In special circumstances, the patient's lab values were excluded from the risk score calculation. The build in the system was originally created to only capture and calculate lab values, which had been obtained within the past 24 hours. If no new lab results were entered within the 24-hour period, the system excluded them from the calculation of the risk score. It should not have been excluding any values older than 24 hours, and should have accounted for lab values further out if needed. The build in the system had to be rebuilt to include lab values older than 24 hours. The current build now pulls the most recent lab values for the current admission, and uses lab values up to 14 days old to calculate the score.

Profile of Population & Sample Design

The population under study to validate the readmissions model included 1,226 Ohio State University James Cancer Hospital & Solove Institute discharged encounters from November 18th, 2015-December 31st, 2015. The Ohio State University James Cancer Hospital & Solove Institute is a 306-bed comprehensive cancer hospital as recognized by the National Cancer Institute. Male and female adult patients (18 and older) with at least one cancer diagnosis were included in the study. Medical and surgical services were the only services included in the study. Patients excluded from the study included patients with benign tumors, those with Sickle Cell disease, patients with a discharge disposition of expired, and any planned readmissions. Benign tumors were excluded because they were not as severe as malignant cancer, and sickle cell was excluded because of the difference in the complexity of the disease. The idea behind the model was to be able to predict unplanned readmissions; therefore, no scheduled and/or planned readmissions were accounted for in the study.

Data Collection Procedures

The beginning validation process of the model included a validation to compare the risk score calculated in the EHR to what the actual score should be, based upon an algorithm created within an Excel database. This was done to ensure the build in the EHR was correctly calculating the patient's risk score. It was important to verify that the

system was calculating the risk score accurately to ensure the model was built correctly and was pulling the correct variables from the Electronic Medical Record (EMR) to calculate the risk score. Since there is a significant gap between IT and clinical terminology, it was important to verify that the translation of terminology did not conflict with the way the build was created. In order to validate that the model was calculating risk scores correctly, file extractions were performed to extract the variables needed to calculate the risk score in Excel, and then compare the two calculated scores.

The variables that were extracted from the EMR included GI cancer diagnoses, the type of service (medical vs. surgical), the length of stay, lab values for hemoglobin, sodium, and white blood cells, any admissions within 60 days, the type of tumor (solid vs. liquid), if there were an emergency admit, and any ED visits within the last 30 days. The hardest variable to extract was the GI cancer diagnosis variable. The descriptions of the patient's cancer diagnosis in his or her problem list were not always clear and had to be clarified by researching the code in an ICD-10-CM codebook. Some times the code driving the code description in the problem list, did not contain the entire code description, and had to be reviewed for clarification.

The length of stay was extracted from the main page of the patient's medical record, and the patient was at a higher risk of readmission if they were in the hospital for more than 5 days. The lab values extracted from the medical record included hemoglobin,

sodium, and the patient's white blood cell count. These variables were all located within the lab values tab in the EMR. To determine if the patient had an admission within the last 60 days, a list of the patient's encounters were reviewed back 60 days from the current admission in attempt to identify any other admissions. The same method was used when trying to locate and identify any ED visits within the last 30 days. In most cases, patients did not have an admission within the past 60 days. When identifying if the patient had an emergency admit, it was also located within the encounters tab of the EMR, and was usually identified when the encounter stated, "ED to inpatient admission". Most encounters were identified as "urgent" rather than "emergency" admissions. If the patient had an "urgent" admission it was defined differently than an "emergency" admission, and did not put a patient at a higher risk.

Data Analysis

The data analysis performed was conducted in the Statistical Software for Social Sciences (SPSS) Version 23.0, Microsoft Excel, and Microsoft Access at The Ohio State University James Cancer Hospital & Solove Institute. Both descriptive and inferential statistical procedures were used for the data analysis.

A Chi-Square analysis was used to demonstrate if there was a significant difference between the high and low risk categories in the model. The significance level used to

determine whether or not there was a significant difference was an alpha level of .05. A Kappa Score was also generated to determine how well the model was performing overall. Descriptive statistics were used to analyze the mean score, the frequency of days from discharge to readmission, the number and percentage of patients that were readmitted into each category (high-risk vs. low-risk), and the number of patients that were included in the study, and determining how many encounters had readmissions. Descriptive statistics were also used to look at the percentage of readmissions based upon their discharge disposition from their initial inpatient stay.

The percentage of readmitted patients were broken out by the service they were on before they were discharged from their initial encounter. The low-risk readmissions were analyzed and file extractions were performed to see if phone calls were placed to the patient from a nurse or PCRM following discharge, if a call was made from a skilled nursing facility and/or home healthcare agency, and also looked to see if the patient, spouse, child, and/or parent called in with questions or concerns regarding the patient's care after discharge.

Chapter Summary

Overall, the data analysis was conducted in various software programs, and descriptive and inferential statistics were used to compile results. Excel was the most

beneficial software used to for the analysis of descriptive statistics and to generate graphs of the results. The large volume of encounters took time to analyze, and the most time consuming part of the research project consisted of the file extractions that were performed. The interpretation of the data analysis and results can be found below in Chapter IV.

Chapter IV: Results

During mid-November 2015 and December 2015, this study was conducted at The Ohio State University James Cancer Hospital & Solove Institute. The study consisted of analyzing data and performing file extractions to validate the cancer readmission model in order to evaluate how well the model performed at predicting readmissions. This chapter summarizes the results of the validation. The statistical analyses was conducted in the Software Package for Social Sciences (SPSS) and additional data analysis and data manipulation was conducted in Microsoft Excel.

Research Questions

Is using the readmissions model and risk score an accurate predictor of hospital readmissions among cancer patients?

After conducting a thorough data analysis, it was found that the model fairly predicts readmissions. In order to inspect how well the model was at predicting readmissions, a Kappa Score was calculated in SPSS. The calculation produced a Kappa Score of 0.125 and can be found below in **Table 2**. The calculated Kappa Score was weak, and demonstrates the model is performing poorly at predicting readmissions and indicates opportunity for improving cutoff categories for high/low risk scores. The overall score was poor, meaning the agreement was not much better than chance. On the Kappa Score range of 0-1, 1 demonstrates a perfect agreement and 0 proves the agreement is no more than chance. With having a low Kappa Score agreement, it shows room for improving the model. The observed agreement was 0.60 and the expected agreement was 0.54.

A chi-square analysis was also conducted, which revealed a p-value of 0.00, meaning there was a significant difference between the high and low risk categories. In the chi-square analysis, it posed that more patients were readmitted from the high-risk category. This demonstrates that the model is predicting readmissions in the correct direction;

however, the predictions were not strong as represented by the Kappa Score calculation.

The chi-square analysis can be found below in **Table 3** and **Table 4**.

Kappa Score Results				
Kappa Value	Asymptotic Standardized Error	Approximate Tb	Approximate Significance	N of Valid Cases
0.125	0.022	5.772	0.000	1226

Table 2: Kappa Score Calculation

Is there a correlation between a higher risk score and the likelihood of readmission?

Out of 1,226 encounters, 176 of them had readmissions. 35.8% of readmissions were within the low risk category, and 64.2% of readmissions were within the high-risk category. The mean score of readmitted patients was -1.9963, and the mean score of those who were not readmitted was -2.2867. The mean scores produced for both the high and low risk categories fell within the cutoff category for high-risk scores. A Chi-Square test was conducted and produced a p-value of 0.00, meaning there is a significant difference between the high and low risk categories.

Chi-Square Test			Cancer Risk Category		Total
			Low	High	
Readmit Flag	No	Count	621	429	1050
		% within Readmit Flag	59.1%	40.9%	100.0%
		% within Cancer Risk Category	90.8%	79.2%	85.6%
	Yes	Count	63	113	176
		% within Readmit Flag	35.8%	64.2%	100.0%
		% within Cancer Risk Category	9.2%	20.8%	14.4%
Total		Count	684	542	1226
		% within Readmit Flag	55.8%	44.2%	100.0%
		% within Cancer Risk Category	100.0%	100.0%	100.0%

Table 3: Chi-Square Analysis

Chi-Square Test			
Test	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	33.313a	1	0.000

Table 4: Chi-Square P-Value

James Readmit Risk Score Flag				
	N	Mean	Std. Deviation	Std. Error Mean
Yes	176	-1.9963	0.56829	0.043
No	1050	-2.2867	0.61721	0.01905

Table 5: High & Low Risk Category Mean Scores

If patients were assigned a low-risk score, but were readmitted, did the discharge disposition have an affect on the readmission?

After reviewing the discharge disposition for both the high and low risk categories, it was found that 62% of the low-risk readmissions were discharged from the initial

inpatient hospital encounter to home/self care, and 27% were discharged from the initial encounter to a home health care agency. In the high-risk category, 42% of patients were discharged home/self care from the initial encounter and 41% received care from a home health care agency. Amongst all categories, only one patient was discharged to receive hospice care. 15% of high-risk readmissions went to a skilled nursing facility; whereas, 9% of low-risk readmissions were discharged to a skilled nursing facility.

Since patients in the low-risk category were more likely to take care of themselves at home, it was no surprise the low-risk category had significantly more encounters with a discharge disposition of home/self care; however, the high percentage of low-risk patients being discharge home could have resulted in patients being readmitted from the low-risk category. Cancer is a complex disease and despite a patient being discharged home with adequate support, it's likely that they struggle reading the signs of the disease and understanding the complex nature of it, making them feel more obligated to return to the hospital for assistance with their care. It could also be a possibility that too many patients in the low-risk category were being discharged home despite having the adequate assistance at home. Home health services and skilled nursing can be expensive, and many patients choose the option to be discharged home, even if it is not the most ideal place for them to return to after discharge. Below, are graphs which represent the number of readmissions, based on the discharge disposition from the initial hospital stay.

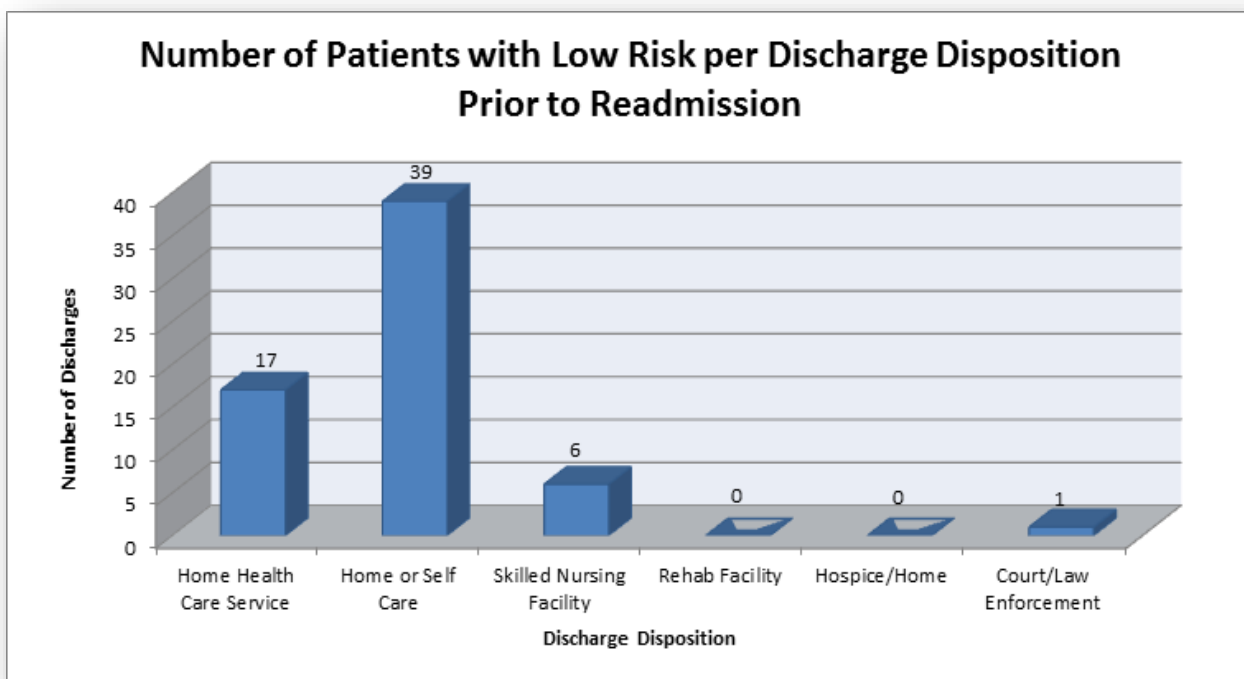


Figure 1: Low-Risk Patients per Discharge Disposition Prior to Readmission

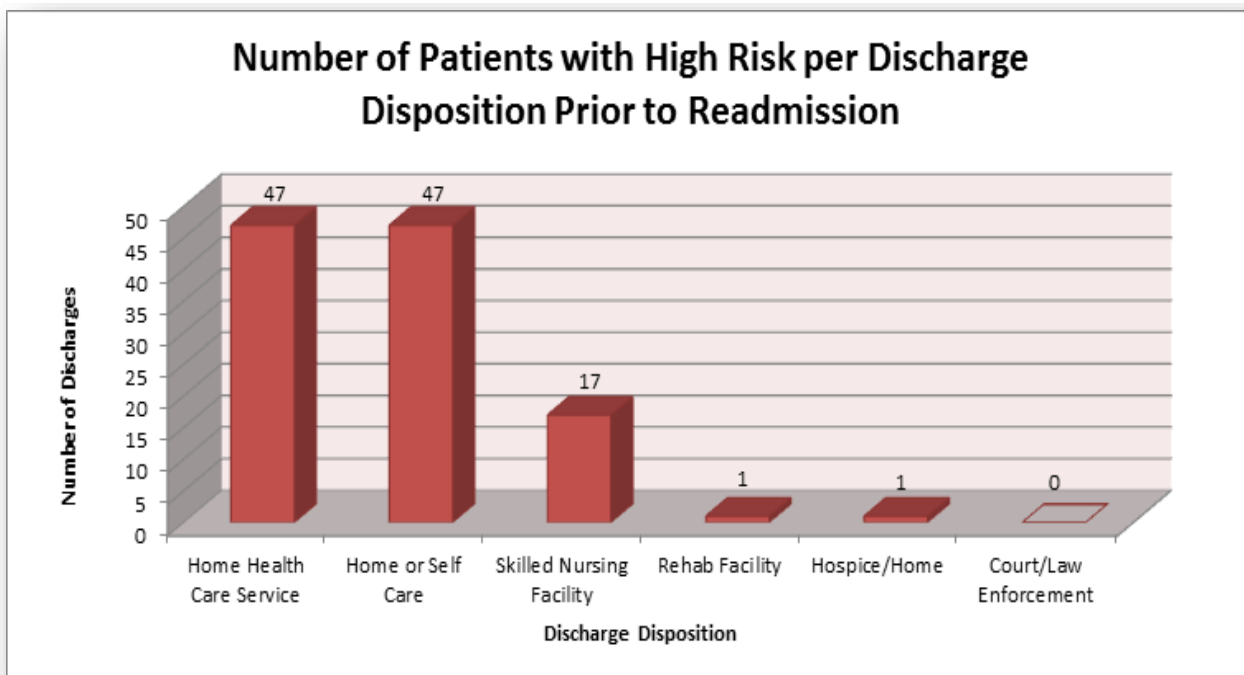


Figure 2: High-Risk Patients per Discharge Disposition Prior to Readmission

Are cancer patients within a particular service area more likely to be readmitted in comparison to those within another service area?

Hematology and Gynecology services had the most unplanned readmissions within the low risk category; whereas, readmissions within the high-risk category and overall readmissions had the highest readmissions within the Hematology, James Hospitalist, and Oncology services. The most common reason for an unplanned readmission was due to complications and the complications varied. Many of the complications consisted of nausea, vomiting, and bleeding. The complications were easily extracted from a Midas Focus Study created for Patient Care Resource Managers (PCRM)s to electronically document a patient's reason for an unplanned readmission. The readmission model put a patient with GI cancer at a higher risk of readmission, but of the 63 readmissions within the low risk category, only one patient was readmitted with a GI service.

There were instances when the predictor was incorrect in the model. There were 429 patients who had high-risk scores but were not readmitted, and there were 63 patients with low risk scores that were readmitted. **Table 6** and **Table 7** below show which services had incorrect predictions for readmissions. The below pie chart reflects the percentage of all discharges by service prior to readmission.

Services with High-Risk Score & Not Readmitted	Count	Percentage
ONCOLOGY	181	42.19%
HEMATOLOGY	99	23.08%
JAMES HOSPITALIST	70	16.32%
BONE MARROW	23	5.36%
COLORECTAL SURGERY	17	3.96%
MED INTENSIVE	12	2.80%
GYNECOLOGY ONCOLOGY	7	1.63%
SUR ONC	6	1.40%
EAR NOSE THROAT	3	0.70%
NEUROONCOLOGY	3	0.70%
SUR THORACIC	3	0.70%
ACUTE CARE SURGERY	1	0.23%
GEN MED 6	1	0.23%
GI SURGERY B	1	0.23%
GS BARIATRICS	1	0.23%
PLASTIC SURGERY 1	1	0.23%
Total	429	100%

Table 6: Services with High-Risk Score & Not Readmitted

Services with Low-Risk Score & Readmitted	Count	Percentage
HEMATOLOGY	21	33%
GYNECOLOGY ONCOLOGY	13	21%
JAMES HOSPITALIST	8	13%
ONCOLOGY	8	13%
UROLOGY	5	8%
COLORECTAL SURGERY	2	3%
ACUTE CARE SURGERY	1	2%
EAR NOSE THROAT	1	2%
GI SURGERY B	1	2%
ORTHO SUR	1	2%
PLASTIC SURGERY 1	1	2%
SUR THORACIC	1	2%
Total	63	100%

Table 7: Services with Low-Risk Score & Readmitted

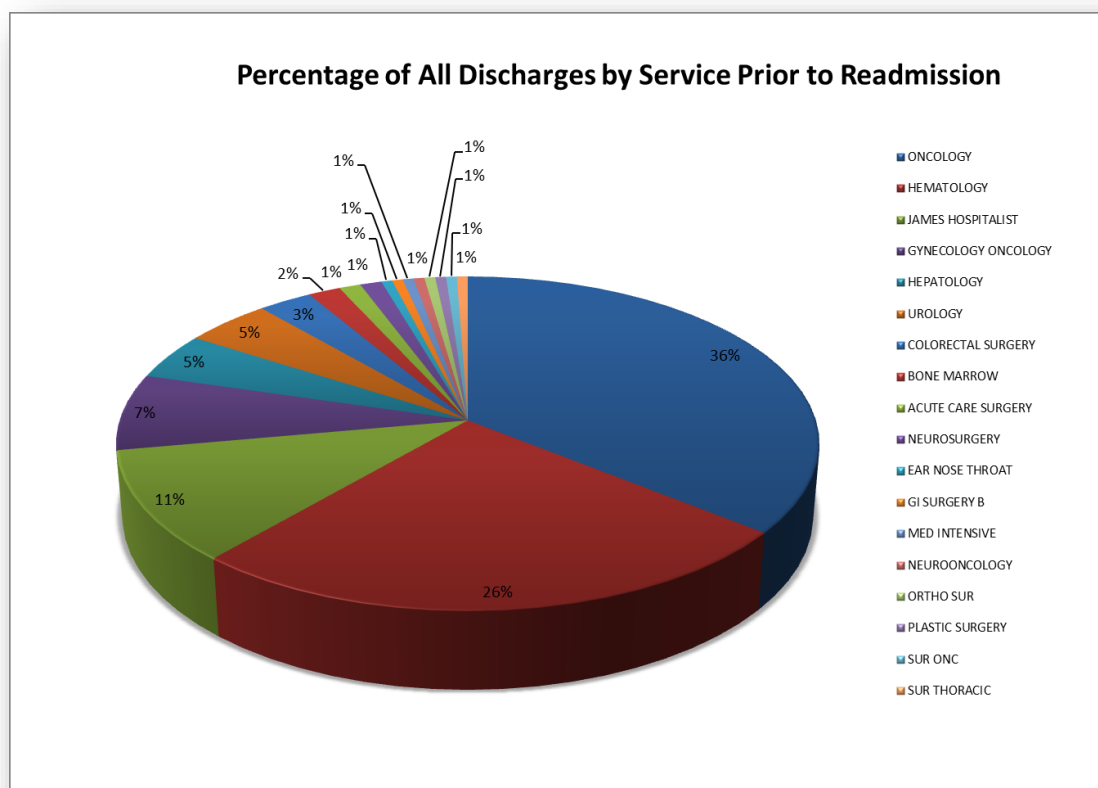


Figure 3: All Discharges by Service Prior to Readmission

Chapter V: Summary

Summary of Findings

After conducting a thorough data analysis, it was found the primary reason for readmissions were due to complications. 81% of readmissions within the low-risk category were readmitted due to complications; whereas, 74% of readmissions in the high-risk category were due to complications. The next three highest areas that resulted in unplanned readmissions included chronic illnesses, disease progression, and post-op complications.

Of all 176 readmissions, the most common discharge disposition prior to the unplanned readmission included discharges to home/self care. 62% of low-risk patients were discharged from their initial encounter, and 42% of high-risk patients were also discharged home/self care. In the high-risk category, the percentage of patients discharged home was very close to the percentage of patients discharged home with home healthcare services. Since high-risk patients require more resources and cannot care for themselves as easily, it was not abnormal to see a higher percentage of patients discharged home with home healthcare services arranged. In the low-risk category, only 27% of were discharged home with home health services. Surprisingly, only one encounter from all readmissions was discharged to hospice. The low number of patients discharged to hospice could be due to the fact that most patients that are critically ill do not get discharged and may require in house hospice care in their final stages.

An analysis was conducted on all discharges by service prior to readmission. Out of all discharges, which led to a readmission, the services that had the most unplanned readmissions were Oncology, Hematology, James Hospitalist, and Gynecology. The count of encounters by service prior to readmission can be summarized in the **Table 8** below.

Service	Count	Percentage
ONCOLOGY	63	36%
HEMATOLOGY	45	26%
JAMES HOSPITALIST	29	16%
GYNECOLOGY ONCOLOGY	13	7%
UROLOGY	8	5%
COLORECTAL SURGERY	5	3%
BONE MARROW	3	2%
ACUTE CARE SURGERY	2	1%
EAR NOSE THROAT	1	1%
GI SURGERY B	1	1%
MED INTENSIVE	1	1%
NEUROONCOLOGY	1	1%
ORTHO SUR	1	1%
PLASTIC SURGERY 1	1	1%
SUR ONC	1	1%
SUR THORACIC	1	1%
Total	176	100%

Table 8: All Readmissions by Prior Service

Between both the high-risk patients and the low-risk patients, the average number of days from discharge to the unplanned readmission was a little over 21 days. The average days until readmission for the high-risk category was 21.67 days, 21.72 for low-risk patients, and 21.66 days for all readmissions combined. The median days from discharge to readmission was 17.0 days for the high-risk category, low-risk category, and overall

readmissions. The number of days from discharge to the unplanned readmission, which had the most frequency were days 2-9 and 14.

The days closest to discharge were the days that patients were more likely to return to the hospital and become inpatient status. This could be due to lack of coordination between the medical staff, lack of patient education an/or patient understanding, or patients being discharged home with no additional services arranged when the patient required more resources to be cared for at home. Since so many patients had a discharge disposition of home, it is likely that patients preferred to be discharged home for peace of mind and without a financial burden. Patients should be aware that cancer is complex and nature can change quickly, and being at home with self care may not always be the most suitable for all conditions.

Of the 63 patients which comprised the low-risk category, 40 of them either called into the hospital to have a question answered and/or a concern addressed. 11 encounters had calls made from either a skilled nursing facility or home healthcare agency, and 14 encounters included a Patient Resource Manager (PCRM) or nurse initiating a call to the patient after discharge. Only two patients had calls from all three categories. From this information, it looks like there is room for improvement with initiating calls to patients post-discharge to check on the status of the patient and address any questions or

concerns. More patients called the James regarding questions than there were outgoing calls to check on the patient.

Overall, 35.8% of readmissions were within the low risk category, and 64.2% of readmissions were within the high-risk category. A higher percentage of patients from the high-risk category were readmitted, which is the result we had hoped to see to demonstrate that the model was predicting readmission accurately. The Chi-Square test produced a p-value of 0.00, which demonstrated a significant difference between the high and low risk categories.

The overall Kappa Score was 0.125 and demonstrates the model is poorly predicting readmissions and indicates opportunity for improving cutoff categories for high/low risk scores. Overall, the readmissions model is not working much better than chance, but is capturing more patients in the high-risk category that were readmitted.

Conclusions

In conclusion, there is work to be done in order to perfect the model, so it is more precise at capturing 30-day unplanned readmissions, and correctly aligning them within the correct category: high or low risk. Moving forward, a reevaluation of the cutoff scores will be needed in order to capture the right patients within the correct categories. A data

analysis will also need to be conducted on a larger encounter volume. The larger the volume, the more data there is to represent the overall reliability and validity of the model. The readmissions model is one of a kind for the world of cancer. With a few updates to the model, working to establish more precise cutoffs to the scoring, and generating a larger volume of encounters, it will enhance the overall performance of the model and will aid in cancer research.

Implications of Study

The study was able to provide data on hospital readmissions and also allowed for the creation of an Access database to track readmissions. Additionally, the data revealed a relationship between high-risk patients and their likelihood of readmission. Furthermore, the study revealed the need for additional education to patients and their families prior to discharge, and that the majority of discharged patients were discharged home despite their category of risk. This demonstrates a need for better evaluation of patients and their needs prior to discharge. It was also found that Oncology and Hematology had the highest percentage of readmissions. Predicting readmissions is important to the HIMS field and the healthcare industry because readmissions are in the spotlight for the Hospital Readmissions Reduction Program. A major implication of the study is that the model provides reliability of predicting readmissions and could aid in reducing the

overall readmission rate. This could also allow for other similar models to be created for specific service lines, and to be implemented in select hospitals across the nation.

Recommendations

The following recommendations have evolved from this study, and are addressed to optimize the discharge planning and follow up as well as to make sure the model is built and working in the most efficient manner.

1. Replication of this study should be done with 12 months of data after the score cutoffs are reevaluated, to allow for a high volume of encounters and a year worth of data.
2. Efforts should be made to follow up with the patients post-discharge. Many patients in the low-risk category called into the hospital to speak to someone in order to have questions and concerns addressed.
3. More education should be communicated to the patient as well as their families to make sure they fully understand their condition and to know what symptoms they will likely have following treatment. Patients should also be advised of symptoms they should watch out for that will require high priority medical attention.
4. A further medical record extraction should be conducted to make sure all data elements and documentation are optimally analyzed for additional information that could aid in the prevention of readmissions.

5. Consult with clinicians, surgeons, and nurses to make sure all variables used in the calculation of the risk score are valuable and to address what further variables could have been included in the risk score calculation.

Summary

Due to the scarcity of a cancer readmissions predictive model, this study was beneficial in demonstrating the potential of predicting readmissions in designated cancer hospitals. As the model is fine-tuned, the predictive model could become more precise at predicting readmissions. Results indicated that the model is the first of its kind in predicting cancer readmissions; however, there is additional work that needs to be conducted to ensure the model is operating in the most efficient way.

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